

Author's Response To Reviewer Comments

Response to the reviewers

In general, we think that the review process strongly improved the paper quality and therefore we would like to thank the reviewers for their constructive suggestions. The answers to the reviewer questions and remarks can be found below the comment, marked in green.

Reviewer1 :

A few points need to be addressed before publishing

1. The authors utilized the Needleman-Wunsch algorithm to generate one-to-one orthologs between human genes and mouse genes. How does the performance of using this algorithm compared to other algorithms i.e., SMap uses BLAST?

We appreciate the reviewer's comment. In our study, we focused on aligning sequences with multiple orthologues listed for each gene in the reference ensemble database. To ensure accurate comparisons, we opted for global alignments since the reference and query sequences are of similar lengths. In the gene set of potential homologues, our aim was to select the orthologue with the highest overall agreement with the reference sequence. We chose them because they are less likely to show false homology [1].

On the other hand, local alignments, as employed in SMap (Blast), have advantages in identifying homologues in species with higher evolutionary distances between evolutionarily distant species [2]. Their purpose is to pinpoint similar sequencing regions within larger sequences. However, they are not suitable for overall sequence conservation of sequences with similar lengths [1].

SMap is specifically designed for defining homologs between species with higher evolutionary distances, but it comes with computational complexity. We focused on comparing well-annotated species with high evolutionary conservation, and we achieved the best results with the Needleman-Wunsch algorithm. OrthoIntegrate. However in order to provide functionality for more distant species we added a parameter to select between global and local alignment. The assignment of one-to-many orthologues. The function BuildOrthologues() now provides an argument alignment_type, which allows us to switch there by switching between the Smith-Waterman and the Needleman-Wunsch algorithm.

2. The authors have shown the application of OrthoIntegrate in the context of heart failure between mice and humans. Could the authors provide more example of using OrthoIntegrate in other disease conditions or between other species to show the versatility of OrthoIntegrate?

We thank the reviewer for this reasonable comment. As suggested, we applied OrthoIntegrate to another species and another disease condition. We obtained single cell data from human mouse and zebrafish for healthy and Alzheimer's conditions and integrated it with OrthoIntegrate. The results are summarized in Suppl. Fig. 6 and an additional paragraph was added to the discussion.

"To further demonstrate the functionality of OrthoIntegrate, we integrated scRNA-SEQ data from human [41], mouse [54] and zebrafish [55] under alzheimer condition. Besides the evolutionary distance between these species, we could jointly cluster different cell types (A-C) and detect commonly expressed marker genes within these cell clusters (Suppl. Fig 6 D-F)."

3. To assess the quality of clustering after integration, the authors calculated silhouette coefficients/scores and found that integration improved clustering performance. Could the authors include more benchmarking metrics to assess the performance of different integration methods? The authors could consider metrics like the species mixing score used by BENGAL (Song et al., 2022, biorxiv; <https://doi.org/10.1101/2022.03.15.481111>; <https://www.biorxiv.org/content/10.1101/2022.03.15.481111v1>; <https://www.genomics.org/doi/abs/10.1101/2022.03.15.481111>)

We would like to thank the reviewer for drawing our attention to the Bengal Paper [3]. We applied all their benchmarking metrics. The results can be seen in Figure 2D. Additionally we added the following paragraph to the discussion section.

"We demonstrated the usability of combining cross-species single cell data by using data sets of human and mouse heart failure. In order to evaluate the species mixing and the biological conservation of different integration methods, we applied certain metrics which were also suggested by Song et.al [3-5]. The results are summarized in Figure 2D. We found that most batch correction methods performed well with OrthoIntegrate.

For biological conservation scores, we demonstrate that some metrics, like the "cell cycle conservation" are improved by using OrthoIntegrate. The variance caused by different cell cycle states of the cells is conserved via OrthoIntegrate. Other parameters like the NMI-score are strongly influenced by the cell type labeling [3], which was focused only on main cell type groups in these datasets. For example, a subpopulation or mixed cell type population clusters. In other words, subclusters of different cell types were not annotated in OrthoIntegrate. In terms of numbers of features that are included in OrthoIntegrate, the clustering might be more diverged, likely by species specific non-

which are not included in the other databases. Therefore, the more divergent clustering, due the increased number of features, the broad cell type labeling might explain the slightly reduced NMI scores. "

4. Miscalling of figures: silhouette coefficients are shown in Supp_Fig_4 rather than Suppl_Fig_3.

We changed the text accordingly and added Supp_Fig_4 to the main manuscript as Fig 2.

5. Some information on the used datasets in the manuscript has been shown in supplementary table 1, but it's still a bit confusing and human HFrEF datasets come from. I am not exactly sure, but I presume HFrEF datasets are from E-MTAB-13264? This information should be explicitly in the method section.

We changed the text accordingly and added detailed information regarding the origin of the samples. Additionally, we added information about the Alzheimer datasets.

Reviewer2:

- [] 1. Ortholog identification has long been a critical and essential step for many comparative, evolutionary, and functional genomics studies. For the performance of an orthology inference method, there are some gold standards available for benchmark testing, such as the Quest Orthology Benchmark Service (<https://orthology.benchmarkservice.org>). Whether OrthoIntegrate outperforms other methods should be comprehensively benchmarked using these metrics, rather than relying solely on the silhouette coefficient score from a heart single-cell RNA sequencing (scRNA-seq) dataset.

According to the reviewer suggestions, we incorporated the Quest Orthology Benchmark Service and tested the 4 orthology datasets. OrthoIntegrate has the second highest Gene Ontology Conservation score and the second highest Enzyme Classification score. The highest score was achieved with InPara.

We tried to perform other tests as well. But since we are only comparing two species and these tests require multi species evaluation, we perform all tests from the Quest Orthology Benchmark Service. The results from the Orthology Benchmark Service were incorporated into the manuscript.

- [] 2. According to the authors' integration pipeline, both human and mouse scRNA-seq data are individually clustered to assign cell types, and then further integrated with orthologous genes for clustering to assign new labels. How do the labels for each cell and each cell type change after integration approach? Does cell type assignment become more reasonable after the integration? The authors should demonstrate that using orthologous genes for clustering improves the accuracy of cell type assignment. The silhouette coefficient score is not a direct metric for cell type assignment, as it is influenced by biological factors. For example, in Supplementary Table 3, the silhouette scores of mouse-HFrEF samples generally are consistently higher than those by OrthoIntegrate, which is opposite to the control groups and human-HFrEF samples.

In order to assign cell type, we manually applied previously established marker genes (Tombor et al. 2021) to assign the human cell types. We used singleR, to transfer cell labels from the human to the mouse samples, based on published marker genes. Furthermore, we applied all benchmarking metrics from the BENGAL paper [3] to our pipeline in order to validate cell type assignment.

We added the following paragraph to the discussion:

"We demonstrated the usability of combining cross-species single cell data by using data sets of human and mouse heart failure samples. In order to evaluate the species mixing and the biological conservation of different integration methods, we applied certain metrics which were also suggested by Song et.al [3-5]. The results are summarized in Figure 3D. We found that most batch correction methods outperform OrthoIntegrate.

For biological conservation scores, we demonstrate that some metrics, like the "cell cycle conservation" are improved by using OrthoIntegrate. The variance caused by different cell cycle states of the cells is conserved via OrthoIntegrate. Other parameters like the NMI-score, for example is strongly influenced by the cell type labeling [3], which was focused only on main cell type groups in these datasets. In subpopulation or mixed cell type population clusters. In other words, subclusters of different cell types were not annotated in OrthoIntegrate. Due to the increased numbers of features that are included in OrthoIntegrate, the clustering might be more diverged, likely by species specific non-conserved features which are not included in the other databases. Therefore, the more divergent clustering, due the increased number of features, the broad cell type labeling might explain the slightly reduced NMI scores. "

- [] 3. The data analysis needs to be expanded further if there are findings with potential biological significance. For example, in Figure 25, we observe a group of genes showing increased expression in human FBs, and we also identify a set of genes that are not expressed in mouse FBs.

human ECs.' However, there is no functional analysis, such as GO or KEGG pathway enrichment analysis, conducted to interpret findings.

We thank the reviewer for the valuable input. To expand the biological significance of the data analysis, we performed gene set enrichment analysis (GSEA) to determine if the genes that are either enriched in humans, mice or genes that are commonly regulated, in all other cell types. Furthermore, we plotted enrichment scores (ES) for each gene. As all these analysis would exceed the scope of the supplementary figure, we uploaded them to the paper specific github account (https://github.com/MarianoRuzJurado/RuzJurado_et_al_2023/tree/main/Expanded_Analysis_Figures). Additionally, we performed GSEA analysis to determine if the genes that were regulated in the fibroblast cluster 25 and endothelial cell cluster 28. The results were incorporated in Figure 4B and 4C accordingly.

- [] 4. The discussion section is confusing. The authors should clarify whether the paper is primarily focused on research methodology or a research analysis paper, the authors should conduct additional investigations to include further data analysis. If it is a research methodology paper, the discussion to relate to the algorithm itself.

According to the reviewers suggestions, we restructured the discussion section and added additional paragraphs regarding the benchmarking of OrthoIntegrate. Additionally we have strengthened the research part by incorporating the benchmarking results from the paper.

Minor comments:

MinorThings:

- [] 1. The cell number for each sample and each clustered cell type is critical for assessing the reliability of the results; how many cells were analyzed in the paper.

We thank the reviewer for this remark and added all QC statistics to the Supplementary Table 6.

- [] 2. As the mouse model is generated through chronic infarction, it raises the question of why very few T/B cell markers are found in the mouse model. 1F. Is it possible that these cell types are not adequately captured in the mouse samples? In data integration analysis, the authors should provide a better understanding how species-specific cell types perform, particularly when, for instance, only macrophages are the dominant immune cells in the mouse model.

We thank the reviewer for this comment. In single nuclei sequencing of isolated hearts, almost no T-cells or B-cells are found in the mouse model. heart cell Atlas by Litviňuková et.al.; Nature 2020 showed mainly Myeloid cells (see <https://www.heartcellatlas.org/v2/global>). In our dataset, we also could not detect any t- or b-cell clusters (see Reviewer Fig.1 in the GitHub Repository [https://github.com/MarianoRuzJurado/RuzJurado_et_al_2023/blob/15e208c336b668402aa201cfc45d6433c1479ea6/Reviewer_Fig1.png]). However, for scientist interest in mouse or human specific immune cell responses through chronic inflammation, we provide our github repository (https://github.com/MarianoRuzJurado/RuzJurado_et_al_2023/tree/main/Expanded_Analysis_Figures/Immune_Cell_Analysis) where immune celltype are analyzed there in detail.

- [] 3. On page 5, clarify "latter ones" in the sentence "Most of the latter ones were long non-coding RNAs with identical gene names".

We clarified the text in this paragraph and changed the sentence to:

"Most of the 86 matches found by lowercasing were long non coding RNAs with identical gene names"

- [] 4. On page 5, correct the reference to Supplementary Figure 4A instead of Supplementary Figure 3A and Supplementary Figure 4B.

We changed the text accordingly and added Supp_Fig_4 to the main manuscript as Fig 2.

- [] 5. On page 16, replace "regulated genes" with "differentially expressed genes (DEGs)" to accurately represent what the authors mean.

We changed the text accordingly.

References

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2. Tanay A, Seb -Pedr s A. Evolutionary cell type mapping with single-cell genomics. *Trends Genet*. 37:919–322021;
3. Song Y, Miao Z, Brazma A, Papatheodorou I. Benchmarking strategies for cross-species integration of single-cell RNA sequencing data. *Nat Commun*. 14:64952023;
4. Otero-Garcia M, Xue Y-Q, Shakouri T, Deng Y, Morabito S, Allison T, et al.. Single-soma transcriptomics of tau-bearing neurons reveals the signatures of tau-associated synaptic dysfunction. *bioRxiv*.
5. Luecken MD, B ttner M, Chaichoompu K, Danese A, Interlandi M, Mueller MF, et al.. Benchmarking atlas-level data integration methods. *Nat Methods*. 19:41–502022;